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Impacts of COVID-19 outbreak on the spillovers between US and Chinese stock sectors

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ABSTRACT

This paper examines the impacts of COVID-19 outbreak on the spillover between ten US and Chinese equity sectors. We use Copula and Conditional Value at Risk approaches. The results show evidence of asymmetric tail dependence during the COVID-19 outbreak with the exception of the Utilities sector, where a symmetric tail dependence is found. Moreover, we find time-varying bidirectional asymmetric risk spillovers from the US to China and vice versa. The risk spillover is higher from the US to China before COVID-19 and from China to the US during COVD-19 spread, which is significantly intensified between March 2020 and April 2020.

1. Introduction

The COVID-19 pandemic has resulted in over 87.6 million confirmed cases and over 1.9 million deaths globally in January 2021, according to the World Health Organization (WHO). The virus spread has severe damages to the global healthcare systems, the real economy, and the financial sphere (Bakas and Triantafyllou, 2020; Goodell, 2020; Ma et al., 2020).[1] The damages of the COVID-19 pandemic surpass those of the 2008 global financial crisis (GFC). The pandemic outbreak has paralyzed the national and international economic activity and financial markets. He et al. (2020) find that the COVID-19 pandemic has negative impacts on stock market returns in the short term. Baker et al. (2020a,2020b) document that the epidemic has unprecedented adverse effects on stock market volatility when compared with the respective impact of various other infectious diseases. Ashraf (2020) concludes that the stock market returns continue to decline as the number of confirmed cases increase. Lyócsa and Molnár (2020) show that the autocorrelation of the S&P 500 index returns increased in magnitude and remained negative in periods of extreme market volatility and when attention to the COVID-19 increased.

Besides, the pandemic has significantly raised the tension between the US and China when the US president has accused the Wuhan Institute of Virology of causing the global epidemic. These factors have considerably increased the uncertainty in the US and Chinese stock markets. This has attracted our attention to better understand and evaluate how risk spreads across the stock sectors in these countries.

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[1] Baumeister and Hamilton (2019) find that the COVID-19 outbreak results in 4.5% decline in the world industrial production during the first quarter of 2020.

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Table 1
Summary statistics for the US and Chinese stock sector returns.

	Mean	Median	Minimum	Maximum	Std.Dev	Skewness	Kurtosis
Panel A. United States							
S & P 500 Index	-0.007	0.051	-12.765	8.968	1.922	-0.892	12.834
Consumer Discretionary	0.003	0.114	-12.876	8.287	1.840	-1.427	13.557
Consumer Staples	0.000	0.023	-9.690	8.075	1.591	-0.213	11.771
Energy	-0.206	0.000	-22.417	15.111	3.036	-1.661	15.875
Financials	-0.080	0.036	-15.071	12.425	2.439	-0.732	11.887
Health Care	0.026	0.060	-10.528	7.314	1.729	-0.353	8.867
Industrials	-0.092	0.000	-12.155	12.001	2.135	-0.670	10.667
Information Technology	0.066	0.121	-14.983	11.300	2.253	-0.623	11.613
Materials	-0.041	0.000	-12.147	11.003	2.096	-0.675	9.599
Telecommunication	0.016	0.122	-11.030	8.802	1.789	-0.809	10.043
Utilities	-0.018	0.072	-12.265	12.320	2.169	-0.096	11.802
Panel B. China							
CSI 300 Index	-0.023	0.000	-9.856	3.738	1.411	-1.521	9.096
Consumer Discretionary	-0.012	0.000	-10.854	4.230	1.649	-1.318	7.039
Consumer Staples	0.078	0.000	-9.012	5.429	1.695	-0.481	3.799
Energy	-0.138	-0.002	-9.721	3.433	1.207	-1.882	13.685
Financials	-0.063	0.000	-9.764	4.657	1.424	-1.258	7.918
Health Care	0.040	0.040	-6.447	3.656	1.529	-0.566	1.722
Industrials	-0.059	0.000	-10.864	5.755	1.468	-1.605	11.455
Information Technology	0.042	0.000	-11.630	6.309	2.194	-0.897	3.789
Materials	-0.058	0.000	-10.871	5.535	1.571	-1.262	8.479
Telecommunication	0.002	0.000	-11.555	7.022	2.271	-0.584	4.113
Utilities	-0.072	0.000	-6.116	2.664	0.942	-1.211	5.968

Notes: The Std. Dev indicates the standard deviation.

The magnitude and the directional of risk spillovers among industry sector groups impact the investment decisions. Moreover, market prices experience periods of downside and upside trends, which affect the investor risk appetite and financial asset pricing. Meric et al. (2008) document that the co-movements and the diversification benefits vary during bear and bull markets.

Previous studies have investigated the relationships within US stock sectors (Livingston 1997;Roll, 1992; Schwartz and Altman, 1973) or among Chinese stock sectors (Hao and He, 2018; Feng et al., 2018; Li et al., 2020; Wu et al., 2019).[2] To the best of our knowledge, this is the first study that examines the impacts of COVID-19 on the dependence structure and upside and downside price spillovers between US and Chinese stock sectors.

Our results show that Energy, Financials, and Materials sectors exhibit tail independence, whereas the remaining sectors reveal tail dependence. Moreover, the COVID-19 pandemic outbreak intensifies the bidirectional price spillovers from the US to China and vice versa. Finally, the spillovers are higher from the US to the Chinese stock sectors before the COVID-19 outbreak and from Chinese to US sectors during the COVD-19 pandemic period. The risk spillovers show a significant abrupt from March 2020 to April 2020.

This study contributes to the literature on two main fronts. First, it examines the impacts of COVID-19 on the dependence structure among stock sectors in the US and China, the two largest stock markets in the world.[3]. We notice that the investment in the Chinese stock market is risky and characterized by high volatility and low returns (Su and Fleisher, 1998). Besides, the Chinese and US stock markets have suffered, in the last decade, from successive crashes. Second, it analyzes the upside and downside risk spillovers from the US to the Chinese sectors and vice versa. We carry out our study at both aggregate and sectoral levels. To achieve our objectives, we use Copula and Conditional Value at Risk (CoVaR) approaches.

Based on the above arguments, studying the linkages among stock sectors of the two power economies is worthy of investigations following the Sino-US trade friction incident in 2018.

The remainder of this paper is organized as follows. Section 2 discusses the materials. Section 3 discusses the empirical results. Section 4 concludes the paper.

2. Materials

2.1. Data and summary statistics

We use daily closing stock prices of China and the United States. Specifically, we consider the S&P 500 Index and CSI 300 Index as aggregate indexes and their corresponding ten sectors (Consumer Staples, Consumer Discretionary, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunication, and Utilities).The CSI 300 Index and S&P 500 Index report the investment performance of the most extensive stocks traded in Shanghai and Shenzhen stock exchanges for China and the US,

[2] A large number of studies has examined the relationships among international aggregate stock markets.

[3] For more details on the stock exchange markets in China and US, the reader can visit http://www.szse.cn/, http://www.sse.com.cn/, and https://us.spindices.com/indices/equity/sp-500

respectively. They are a benchmark for international investors on the financial health of the global stock market. The sample period spans from April 1, 2019, to May 14, 2020. We select this period to stress on the COVID-19 effects. More precisely, we consider two subsamples of data. One runs from April 1, 2019, to November 29, 2019, and the second one runs from December 1, 2019, to May 14, 2020, to investigate the dependence structure and spillovers before and during the effects of the COVID-19 pandemic. The data are compiled from Bloomberg. The time variations of daily price returns of all markets show high volatility clustering and fat tails, which is higher in China than in the US.[4]

Table 1 presents the descriptive statistics of stock price returns. We observe that the average returns are negative for all markets (except for Consumer Staples, Information Technology, Telecommunication, Health Care, and US Consumer Discretionary). The US stock sectors are generally riskier than the Chinese markets. All return series deviate from normal distributions. The correlations among all pairs are positive and range between 0.14 for the Telecommunication sector and 0.32 for the Financials sector (Table 2).

2.2. Empirical methods

2.2.1. Copula

We consider seven types of copulas, summarized in Table 3, to capture the time-varying dependence features. We follow the two-step process to estimate the Copula and marginal density parameters. The joint density function $f_{XY}(x,y)$ is:

$$f_{XY}(x,y) = c(u,v)f_X(x)f_Y(y) \tag{1}$$

where $c(u, v)$, is copula density and $f_X(x)f_Y(y)$ are X and Y's marginal densities.

2.2.2. CoVaR

To measure the risk spillovers, we use the CoVaR measure of Adrian and Brunnermeier (2016) to provide the information on the VaR of a market conditional of the fact that another market is in financial distress.

Let r_t^U be the returns for the US equity market and r_t^C be the returns for China's equity market. The downside CoVaR for the returns of the US equity market given an extreme downward trend in returns of an equity market at a confidence level of$(1 - \beta)$ or β-quantile of the conditional distribution of r_t^U is as follows:

$$Pr\left(r_t^U \leq CoVaR_{\beta,t}^U | r_t^C \leq VaR_{\alpha,t}^C\right) = \beta \tag{2}$$

Likewise, the upside CoVaR is as follows:

$$Pr\left(r_t^U \geq CoVaR_{\beta,t}^U | r_t^C \geq VaR_{1-\alpha,t}^C\right) = \beta \tag{3}$$

Combining the copula measure, CoVaR in Equations (3)–(4) as follows:

$$C\left(F_{r_t^U}\left(CoVaR_{\beta,t}^U\right),\ F_{r_t^C}\left(VaR_{\alpha,t}^C\right)\right) = \alpha\beta \tag{4}$$

$$1 - F_{r_t^U}\left(CoVaR_{\beta,t}^U\right) - F_{r_t^C}\left(VaR_{t-\alpha,t}^C\right) + C\left(F_{r_t^U}\left(CoVaR_{\beta,t}^U\right), F_{r_t^C}\left(VaR_{1-\alpha,t}^C\right)\right) = \alpha\beta \tag{5}$$

where $F_{r_t^U}$ and $F_{r_t^C}$ are the marginal distributions of US and Chinese equity market returns, respectively.

3. Empirical results

3.1. Dependence structure analysis

Tables 4 and 5 report the results of time-varying copulas before and during COVID-19 outbreak, respectively. The results of time-invariant copulas are available upon request. Using Akaike information criteria (AIC), we find that the time-varying Copula outperforms the time-invariant Copula for all cases.[5] During the pre-COVID-19 outbreak, the results show a significant positive average dependence for Financials, Health Care, and Industrials sectors, as given by TVP-Gaussian copula. This result indicates independence for these three sectors during bear and bull market conditions, suggesting that Financials, Health Care, and Industrials sectors serve as a diversifier, hedge, and safe-haven asset. For aggregate index and Consumer Staples, we find a dynamic symmetric tail dependence as modeled by TVP-Student-t copula, suggesting the same co-dependence during the bullish and bearish market. In contrast, Consumer Discretionary and Telecommunication exhibit a positive lower tail dependence during the bearish market and upper tail independence during the bullish market as given by TVP Clayton copula, indicating that US and Chinese Consumer Discretionary and Telecommunication sectors co-crash during the crash period. The Utilities sector shows an upper tail dependence and lower tail independence,

[4] The figure of time variations of aggregate and disaggregate stock prices and stock price returns are available upon request.

[5] We notice that the standardized residuals are used for time-varying parameter (TVP) copula estimations which are generated from best-fitted marginal model ARMA (p, q)-TGARCH (1, 1). The best-fit copulas are selected based on minimum of AIC values.

Table 2.
Correlation matrix between US and Chinese equity sectors.

	aggregate	Consumer Staples	Consumer Discretionary	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecommunication	Utilities
$\rho_{i,j}$	0.30	0.17	0.27	0.29	0.32	0.19	0.31	0.24	0.29	0.14	0.18

Notes: This table presents the linear correlations among US and China equity sectors.
$\rho_{i,j}$represents the correlation coefficient between sector i and sector j.

Table 3
The summary of copula models and their tail dependences.

Copula models	Copula function	Parameter	Tail dependence
Gaussian	$C_N(u_1,u_2;\ \rho) = \Phi_\rho[\Phi^{-1}(u_1),\Phi^{-1}(u_2)]$	$\rho \in [-1, 1]$	$\lambda_U = \lambda_L = 0$
Clayton's	$C_C(u_1,u_2;\theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}$	$\theta \in [-1, +\infty)$	$\lambda_L = 2^{-1/\theta}$, $\lambda_U = 0$
Rotated Clayton	$C_{RC}(u_1,u_2;\ \theta) = ((1-u_1)^{-\theta} + (1-u_2)^{-\theta} - 1)^{-1/\theta}$	$\theta \in [-1, +\infty)$	$\lambda_L = 0$, $\lambda_U = 2^{-1/\theta}$
Gumbel	$C_G(u_1,u_2;\ \delta) = \exp(-((-\ln u_1)^{\delta} + (-\ln u_2)^{\delta})^{1/\delta})$	$\delta \in [1, \infty)$	$\lambda_L = 0$, $\lambda_U = 2 - 2^{1/\delta}$
Rotated Gumbel	$C_{RG}(u_1,u_2;\ \delta) = u_1 + u_2 - 1 + C_G(1-u_1,1-u_2;\ \delta)$	$\delta \in [1, \infty)$	$\lambda_L = 2 - 2^{1/\delta}$, $\lambda_U = 0$
Student-t	$C_{ST}(u_1,u_2;\rho,\nu) = t_{\rho,\nu}[t_\nu^{-1}(u_1),t_\nu^{-1}(u_2)]$	$\rho \in [-1, 1]$	$\lambda_U = \lambda_L = 2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{1-\rho}/\sqrt{1+\rho})$
SJC	$C_{SJC}(u_1,u_2;\ \tau_U,\tau_L) = 0.5(C_{JC}(u_1,u_2;\lambda_U,\lambda_L) + C_{JC}(1-u_1,1-u_2;\tau_U^{JC},\tau_L^{JC}) + u_1 + u_2 - 1)$ $C_t^{JC}(u_t,u_t;\tau_U^{JC},\tau_L^{JC}) = 1-(1-([1-(1-u_1)^k]^{-\gamma} + [1-(1-u_2)^k]^{-\gamma} - 1)^{-1/\gamma})^{1/k}$	$\lambda_U \in (0, 1)\lambda_L \in (0, 1)$	$\lambda_U = \tau_U$, $\lambda_L = \tau_L$

Notes: λ_L and λ_U denote the lower and upper tail dependence, respectively. For the Gaussian Copula, $\Phi^{-1}(u_1)$ and $\Phi^{-1}(u_2)$ are the standard normal quantile functions and Φ is the bivariate standard normal cumulative distribution function with correlation ρ. For the Student-t copula, $t_\nu^{-1}(u_1)$ and $t_\nu^{-1}(u_2)$ are the quantile functions of the univariate Student-t distribution with ν as the degree-of-freedom parameter. For the SJC copula, $k = 1/\log_2(2-\lambda_U)$, $\gamma = -1/\log_2(\lambda_L)$. This table provides the brief summary of different copula functions used in the study.

as shown by TVP Rotated Clayton copula, suggesting that the Utilities sector is a safe haven asset. The Energy, Information Technology, and Materials sectors exhibit asymmetric tail dependence as defined by TVP-SJC copula.

During the COVID-19 pandemic period, we observe asymmetric tail dependence for five-out-of-ten sectors, namely Consumer Staples, Energy, Financials, Health Care, and Industrials. The utilities sector shows symmetric tail dependence, indicating that the co-dependence differs during bearish and bullish markets. This result exhibits that investors should adjust their portfolio according to the market conditions. Information Technology exhibits independence during bearish markets, indicating the role of this asset as a safe haven during downside market status. A similar result is obtained for Telecommunication and Consumer Staples. Finally, the aggregate index exhibits a lower tail dependence and upper tail independence, as modeled by TVP Clayton copula. The evolving dependence among US and Chinese sectors is explained by the occurrence of financial shock events, the frequent changes in the regional and global business cycles, the trade war between the US and China as well as the global health crisis.

3.2. Spillovers analysis

Monitoring the risk spillovers during different market conditions is essential for portfolio management. This study quantifies the downside/upside spillovers from the US to Chinese markets (Panel A of Tables 6 and 7) and from Chinese to US markets (Panel B of Tables 6 and 7). The upside VaRs for the US sectors are much higher than those for those of China, except for the aggregate index, Energy, and Utilities during the pre-COVID-19 period. This result implies that the US sectors are riskier than their Chinese counterparts during bull market conditions. Similarly, the downside VaRs for US sectors are higher than those for China for nine out of ten sectors (except for Energy). The upside CoVaR values are superior to the upside VaRs, indicating significant bidirectional risk spillovers from the US to Chinese sectors and vice versa during bullish markets. More importantly, the upside risk spillover from the US to China is more pronounced than those from China to the US for the aggregate index and nine sectors (except for the Energy sector). Regarding downside VaRs and CoVaRs, we find risk spillovers from the US to China for only Consumer Discretionary, Energy, Materials, and Telecommunications. In contrast, we find insignificant downside risk spillovers from China to the US. More importantly, the values of upside and downside VaRs and CoVaRs are higher during the COVID-19 pandemic relative to the pre-COVID-19 pandemic. The upside and downside risk spillovers thus jumps significantly during the virus pandemic outbreak, suggesting that the global health crisis has a significant impact on the bidirectional spillovers among sectors under investigations. Equity investors and portfolio managers should be cautious on the effects of a global health crisis when they build their portfolios.

Figs. 1 and 2 display the trajectory of downside/upside VaRs and CoVaRs before and during the COVID-19 pandemic outbreak, respectively. The graphical evidence confirms the results of Tables 6 and 7. As we can see, we observe significant time-varying bidirectional risk spillovers. Moreover, the magnitude and the direction of risk spillovers vary across sectors. The risk spillover from the US to China is much higher than those from China to the US during pre-COVID-19. In contrast, during COVID-19, the risk spillover is more pronounced from China to the US than from the US to China. More interestingly, we find significant abrupt changes in risk spillovers during February, March, and April 2020 for all sectors. The increase in spillovers during the COVID-19 outbreak is explained by investor sentiment, which affects the investment decisions and, as a result, the stock pricing. Our results are in line with the study by Ichev and Marinč (2018) as they research the geographic proximity of information during the 2014–2016 Ebola outbreak. It also confirms the findings of He et al. (2020) in which they show significant bi-directional spillovers between Asian, European, and American stock markets.

We use the Kolmogorov-Smirnov (KS) test (Abadie, 2002) to check the robustness of our results and test the hypothesis of no systemic impact between sectors. The results (see the fourth and the last columns of Tables 6 and7) show a significant difference

Table 4.
Estimation results of TVP- copulas between US and Chinese stock sector pairs (Pre-COVID-19).

	Aggregate	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care
1. TVP-Gaussian						
Ψ_0	0.656***	0.047***	-0.115***	0.141***	0.984***	-0.016**
	(0.302)	(0.049)	(0.212)	(0.061)	(0.348)	(16.444)
Ψ_1	1.079***	-0.144***	0.457***	-0.315***	0.877***	-0.333***
	(0.474)	(0.135)	(0.634)	(0.154)	(0.670)	(68.783)
Ψ_2	-2.074***	1.892***	-0.007	1.890***	-2.122***	2.258***
	(0.118)	(0.260)	(2.167)	(0.141)	(0.336)	(21.470)
AIC	-11.872	-5.621	-1.304	-21.338	**-16.954**	**-18.971**
2. TVP-Clayton						
Ω	1.070***	0.130***	0.417***	0.787***	0.955***	-0.278
	(0.702)	(0.000)	(1.278)	(0.770)	(0.789)	(2.274)
A	-0.160***	1.076***	0.091	-0.365***	-0.238***	1.290***
	(0.721)	(0.873)	(6.625)	(1.380)	(1.113)	(1.214)
B	-1.777***	0.303***	-0.988***	-0.759***	-1.009***	1.090***
	(1.978)	(0.000)	(3.283)	(2.337)	(2.032)	(4.625)
AIC	-7.133	**-8.114**	-0.004	-5.674	-10.789	-1.386
3. TVP-Rotated Clayton						
ω_U	0.661***	1.165***	-0.000	0.605***	0.096**	0.000
	(0.810)	(0.609)	(0.983)	(0.509)	(0.506)	(0.999)
α_U	-0.675***	-0.028	-1.107***	-0.512***	-0.080	-1.045***
	(2.005)	(1.021)	(1.165)	(0.612)	(0.757)	(1.011)
β_U	0.206	-3.992***	0.000	0.863***	1.835***	-0.000
	(2.029)	(1.756)	(1.960)	(1.402)	(1.951)	(3.163)
AIC	-8.735	-1.223	0.034	-16.564	-13.532	0.035
4. TVP-Gumbel						
Ω	0.303	1.076***	2.406***	-0.674***	0.451***	-0.000
	(3.602)	(2.299)	(8.088)	(0.046)	(1.510)	(11.256)
A	0.139	-0.519***	-2.384***	0.927***	-0.267**	0.000
	(2.975)	(1.973)	(7.561)	(0.032)	(1.378)	(10.981)
B	-0.239***	-0.942***	-0.025	0.055***	1.091***	0.000
	(1.018)	(2.331)	(1.324)	(0.021)	(1.451)	(2.457)
AIC	-10.676	-1.582	-0.366	-15.971	-12.938	-0.122
5.TVP Rotated Gumbel						
ω_L	0.936***	-0.980	3.218***	1.693***	0.844	2.218***
	(1.476)	(52.744)	(8.280)	(0.716)	(8.277)	(5.566)
α_L	-0.170**	1.070	-3.205***	-1.176***	-0.315	-1.898***
	(1.045)	(133.601)	(7.433)	(0.561)	(6.911)	(5.212)
β_L	-1.226***	0.418	-0.015	0.122	-0.092	-0.378***
	(1.389)	(311.830)	(2.090)	(1.015)	(1.392)	(1.764)
AIC	-8.687	-6.990	-0.730	-7.514	-11.787	-0.529
6. TVP-SJC						
ω_U	-2.027***	-13.232	-16.706***	-2.974***	-9.886***	-19.346***
	(3.207)	(239.654)	(1.906)	(0.227)	(10.340)	(10.953)
α_U	-1.032**	-1.287	-0.000	2.521***	25.000***	-0.000
	(6.022)	(79.551)	(1.000)	(0.556)	(28.754)	(1.000)
β_U	2.794**	-0.005	-0.000	4.498***	-1.039***	-0.000
	(18.603)	(1.043)	(1.000)	(0.182)	(3.969)	(1.000)
ω_L	3.195***	-3.281***	-15.687***	-14.849***	1.419***	-14.923
	(2.116)	(0.000)	(1.534)	(54.166)	(4.325)	(261.560)
α_L	-18.705***	0.745	-0.000	-8.345**	-11.281***	-1.764
	(10.507)	(923.095)	(1.006)	(54.825)	(14.274)	(81.306)
β_L	-8.865***	8.650	-0.000	-0.020	-2.204***	-0.006
	(6.644)	(815.406)	(1.000)	(1.007)	(9.766)	(1.041)
AIC	-12.565	-5.393	1.548	**-24.111**	-15.777	1.026
7. TVP-Student's-t						
Ψ_0	0.469***	0.018***	-0.230***	0.754***	0.329***	-0.014*
	(0.322)	(0.005)	(0.224)	(0.403)	(0.982)	(0.098)
Ψ_1	0.819***	-0.121***	0.754***	0.469***	0.145***	-0.224***
	(0.372)	(0.044)	(0.380)	(0.313)	(0.429)	(1.077)
Ψ_2	-2.026***	2.190***	-0.709***	-2.130***	0.643**	2.278***
	(0.094)	(0.066)	(0.845)	(0.064)	(4.131)	(1.963)
N	5.000***	4.981***	5.000***	5.000***	5.000***	4.917***
	(1.937)	(1.757)	(1.363)	(1.167)	(1.448)	(11.090)
AIC	**-15.804**	-6.783	**-1.397**	-7.527	-8.784	-15.932

Notes: The table displays the fit of multiple copulas with time-varying parameters. In identifying the Copula the best fits the data, we employ the Akaike information criterion (AIC), "The symbols *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4. (*to be continued*)

Industrials	Information Technology	Materials	Telecommunication	Utilities

(*continued on next page*)

Table 4. (*continued*)

	Aggregate	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care
1. TVP-Gaussian						
Ψ_0	0.040	0.675***	0.885	0.268***	-0.012***	
	(0.033)	(0.331)	(0.486)	(0.354)	(0.179)	
Ψ_1	-0.212	1.279***	1.539	0.457***	0.034	
	(0.107)	(0.643)	(0.939)	(0.626)	(0.514)	
Ψ_2	2.161***	-2.042***	-2.268***	-0.750***	-0.136*	
	(0.057)	(0.135)	(0.142)	(2.560)	(5.749)	
AIC	**-16.729**	-10.977	-14.016	-2.498	0.027	
2. TVP-Clayton						
Ω	0.557***	1.457***	0.925***	1.619***	0.765***	
	(0.523)	(0.718)	(0.810)	(0.458)	(1.262)	
A	-0.786***	-0.262***	-0.185***	-0.826***	-0.391***	
	(0.372)	(0.559)	(0.903)	(0.249)	(1.708)	
B	0.736***	-2.982***	-1.245***	-3.366***	-2.345***	
	(1.686)	(2.143)	(2.451)	(1.278)	(3.814)	
AIC	-9.371	-9.749	-7.510	**-5.018**	-0.072	
3. TVP-Rotated Clayton						
ω_U	-0.119**	1.404***	-1.282***	1.545***	-0.527***	
	(0.606)	(0.832)	(0.494)	(0.541)	(0.082)	
α_U	-0.605***	-0.803***	-0.493***	-0.911***	-1.606***	
	(0.425)	(0.352)	(0.197)	(0.362)	(0.293)	
β_U	2.485***	-2.567***	6.674***	-3.595***	3.091***	
	(1.788)	(3.182)	(1.627)	(1.241)	(0.452)	
AIC	-9.391	-6.603	-12.229	-2.299	**-5.106**	
4. TVP-Gumbel						
Ω	0.824***	0.823***	1.540***	2.433***	0.461***	
	(0.836)	(2.023)	(0.392)	(0.337)	(0.878)	
A	-0.837***	-0.041	-1.115***	-1.338***	-1.436***	
	(0.601)	(1.385)	(0.227)	(0.552)	(0.501)	
B	1.721***	-1.455***	0.895***	-2.528***	3.624***	
	(1.511)	(2.091)	(1.693)	(0.923)	(1.266)	
AIC	-10.115	-8.792	-11.443	-2.213	-2.617	
5.TVP Rotated Gumbel						
ω_L	1.257***	1.324***	0.543*	2.299***	-1.163***	
	(0.737)	(1.269)	(3.867)	(0.358)	(1.069)	
α_L	-0.959***	-0.263***	-0.070	-1.202***	0.415***	
	(0.458)	(0.792)	(3.151)	(0.425)	(1.198)	
β_L	0.944***	-2.222***	-0.213*	2.220***	2.283***	
	(1.305)	(1.739)	(1.628)	(1.097)	(1.785)	
AIC	-10.948	-10.511	-8.262	-3.914	-0.636	
6. TVP-SJC						
ω_U	-7.929***	-1.120***	-8.368***	-19.131	-18.403	
	(3.725)	(1.066)	(6.359)	(1538.897)	(2085.066)	
α_U	18.209***	-8.146***	25.000***	-2.015	-2.713	
	(8.717)	(6.010)	(18.131)	(507.421)	(502.264)	
β_U	-10.301***	5.695***	-3.328***	-0.006	-0.018	
	(11.502)	(2.856)	(3.227)	(1.857)	(3.439)	
ω_L	-0.593*	4.221***	2.178***	5.402***	-16.416	
	(4.021)	(3.383)	(2.582)	(18.042)	(312.862)	
α_L	-3.713***	-21.549***	-18.882***	-25.000***	-0.907	
	(12.314)	(16.172)	(11.791)	(69.996)	(95.235)	
β_L	-2.037**	-4.554***	-1.318***	-8.363***	-0.003	
	(11.722)	(2.764)	(2.857)	(11.378)	(1.047)	
AIC	-13.066	**-12.515**	**-14.607**	-4.556	0.960	
7. TVP-Student's-t						
Ψ_0	0.495***	0.679***	0.771***	0.120***	-0.098***	
	(1.164)	(0.361)	(0.523)	(0.261)	(0.236)	
Ψ_1	0.079***	0.475***	0.718***	0.176***	0.191***	
	(0.339)	(0.397)	(0.577)	(0.347)	(0.389)	
Ψ_2	-0.320	-1.964***	-2.140***	0.403*	-0.605***	
	(5.560)	(0.233)	(0.182)	(2.926)	(2.083)	
N	5.000***	5.000***	5.000***	5.000***	5.000***	
	(1.730)	(1.729)	(1.382)	(1.348)	(1.535)	
AIC	-8.719	-8.658	-7.795	4.792	2.867	

Notes: The table displays the fit of multiple copulas with time-varying parameters. In identifying the Copula the best fits the data, we employ the Akaike information criterion (AIC), "*, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5.
Estimation results of TVP- copulas between US and Chinese stock sector pairs (During-COVID-19).

	Aggregate	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care
1. TVP-Gaussian						
Ψ_0	0.499***	0.540***	1.141***	1.668***	0.984***	0.068***
	(1.149)	(1.209)	(0.488)	(0.474)	(0.038)	(0.149)
Ψ_1	-0.176*	-2.000**	-0.546***	-1.368***	0.048**	0.579***
	(0.772)	(0.726)	(0.748)	(1.091)	(0.059)	(0.535)
Ψ_2	0.478*	0.552**	-1.870	-1.467***	2.430***	1.110***
	(3.581)	(3.433)	(0.823)	(0.901)	(0.110)	(0.849)
AIC	-8.869	-11.085	-7.471	-16.862	-20.781	-7.545
2. TVP-Clayton						
ω	-1.274***	0.893***	-0.272***	1.257***	0.320***	-1.684***
	(0.586)	(3.705)	(0.250)	(0.020)	(0.789)	(0.549)
α	0.651***	-0.915	-0.914***	-0.913***	0.439***	-0.277***
	(0.114)	(13.291)	(0.144)	(0.055)	(1.113)	(0.160)
β	4.737***	0.354	4.462***	-0.921***	0.756***	7.067***
	(1.817)	(3.914)	(1.123)	(0.025)	(2.032)	(1.594)
AIC	**-16.093**	-12.207	-14.308	-19.264	-17.491	-14.782
3. TVP-Rotated Clayton						
ω_U	-1.179***	1.108***	-1.281***	2.193***	0.364***	1.131***
	(0.666)	(0.104)	(1.093)	(0.565)	(0.524)	(0.677)
α_U	-0.402***	-1.056***	0.149***	-0.681***	-0.446***	-0.923***
	(0.283)	(1.021)	(0.295)	(0.126)	(0.122)	(0.484)
β_U	6.896***	0.341***	6.115***	-4.410***	2.686***	-1.519***
	(2.203)	(1.038)	(3.797)	(1.969)	(1.940)	(2.627)
AIC	-14.378	**-22.870**	-5.020	-13.728	-15.776	-2.930
4. TVP-Gumbel						
ω	-0.677***	-0.398***	-0.859***	-0.705***	0.139*	-1.002***
	(0.473)	(0.525)	(0.923)	(0.164)	(0.873)	(0.000)
α	0.190***	0.218***	0.050	0.846***	0.264***	0.878***
	(0.574)	(0.404)	(0.560)	(0.071)	(0.724)	(0.000)
β	3.166***	2.247***	4.324***	0.486***	0.386***	1.127***
	(2.407)	(1.593)	(2.905)	(0.352)	(0.829)	(0.125)
AIC	-13.756	-14.151	-7.124	-12.893	-16.594	-8.757
5.TVP Rotated Gumbel						
ω_L	-1.870***	-0.750***	1.316***	-0.682***	-0.183***	-2.197***
	(0.289)	(0.092)	(0.390)	(0.351)	(0.234)	(0.397)
α_L	0.809***	0.780***	-1.090***	0.604***	0.464***	0.626***
	(0.125)	(0.120)	(0.271)	(0.169)	(0.261)	(0.193)
β_L	3.909***	0.945***	1.648***	1.441***	0.609***	4.999***
	(1.282)	(0.489)	(1.022)	(1.466)	(0.709)	(1.246)
AIC	-15.734	-14.440	-10.824	-14.329	-17.459	-14.949
6. TVP-SJC						
ω_U	-5.453***	-3.644***	-14.034***	4.138***	-2.109***	4.529***
	(14.222)	(3.038)	(1.906)	(1.745)	(0.728)	(9.062)
α_U	14.308***	8.029***	-0.001	-16.816***	-1.540***	-25.000***
	(34.862)	(8.493)	(1.000)	(9.156)	(3.063)	(58.852)
β_U	0.174	0.874***	-0.000	-6.574***	5.391***	-6.920***
	(7.558)	(3.178)	(1.000)	(5.430)	(2.117)	(5.512)
ω_L	3.713	-11.718***	-4.805***	-10.914***	-2.916***	-12.393***
	(222.080)	(43.168)	(1.534)	(16.253)	(0.451)	(5.207)
α_L	-25.000	25.000***	18.149***	24.999***	3.737***	25.000***
	(936.400)	(93.675)	(1.006)	(42.917)	(1.446)	(11.777)
β_L	-4.970	6.205***	-6.699***	4.609***	3.754***	5.735***
	(183.690)	(15.475)	(1.000)	(1.740)	(0.664)	(1.759)
AIC	-12.732	-14.955	**-14.976**	**-22.489**	**-21.969**	**-19.135**
7. TVP-Student's-t						
Ψ_0	1.366***	0.763***	0.996***	1.576***	1.160***	-0.034***
	(0.179)	(0.456)	(0.613)	(0.371)	(1.314)	(0.135)
Ψ_1	1.167***	0.509***	-0.291***	-0.521***	0.235***	0.604***
	(0.328)	(0.413)	(0.554)	(0.572)	(0.545)	(0.500)
Ψ_2	-2.637***	-2.329***	-1.399***	-2.304***	-1.022**	1.079***
	(0.322)	(0.117)	(1.672)	(0.110)	(3.297)	(0.884)
ν	4.834***	4.960***	5.000***	5.000***	5.000***	5.000***
	(1.174)	(2.559)	(2.346)	(1.642)	(1.788)	(2.118)
AIC	-11.711	-19.403	-7.017	-18.715	-15.277	-6.869

Notes: The table displays the fit of multiple copulas with time-varying parameters. In identifying the Copula the best fits the data, we employ the Akaike information criterion (AIC), "The symbols *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5. (*to be continued*)

	Industrials	Information Technology	Materials	Telecommunication	Utilities

(*continued on next page*)

Table 5. (*continued*)

	Aggregate	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care
1. TVP-Gaussian						
Ψ_0	0.924***	0.387***	0.623***	0.315***	-0.125***	
	(1.192)	(0.317)	(0.458)	(0.368)	(0.179)	
Ψ_1	-0.423***	0.560***	1.550***	0.628***	1.614***	
	(0.810)	(0.638)	(0.610)	(0.788)	(0.514)	
Ψ_2	-0.246	-0.449***	-2.119***	-1.620***	-1.608***	
	(2.949)	(1.337)	(0.108)	(0.776)	(5.749)	
AIC	-12.278	-3.613	-9.611	-1.244	-7.686	
2. TVP-Clayton						
ω	-0.121***	1.299***	-1.681***	0.983***	0.785***	
	(0.494)	(0.687)	(0.882)	(1.027)	(0.435)	
α	0.174***	-0.271***	0.327***	-1.562***	-0.965***	
	(0.285)	(0.769)	(0.101)	(1.278)	(0.246)	
β	2.729***	-2.709***	6.841***	-1.798***	-0.024	
	(1.961)	(1.848)	(2.581)	(2.866)	(0.943)	
AIC	-13.191	-2.050	-9.908	-0.248	-3.241	
3. TVP-Rotated Clayton						
ω_U	-1.046***	0.126***	0.302***	-1.282***	2.086***	
	(0.932)	(0.192)	(0.801)	(0.678)	(0.419)	
α_U	0.070***	0.618***	0.205	0.901***	-1.180***	
	(0.205)	(0.069)	(1.479)	(0.403)	(0.208)	
β_U	5.938***	0.637***	0.570**	3.248***	-4.707***	
	(3.350)	(0.334)	(2.553)	(1.275)	(0.956)	
AIC	-16.910	-10.157	-5.041	**-5.233**	-5.100	
4. TVP-Gumbel						
ω	-0.783***	-0.769***	-0.189	-1.972***	-0.475***	
	(0.538)	(1.398)	(1.642)	(1.147)	(0.550)	
α	0.129***	0.733***	0.358***	1.102***	0.923***	
	(0.310)	(0.125)	(1.391)	(0.443)	(0.323)	
β	4.057***	0.822***	0.591***	2.294***	-0.749***	
	(2.623)	(2.427)	(1.879)	(1.528)	(0.715)	
AIC	-18.059	**-10.485**	-4.682	-4.749	-5.774	
5.TVP Rotated Gumbel						
ω_L	-0.480***	1.314***	-0.679***	-2.483***	-0.462***	
	(0.402)	(1.462)	(0.721)	(0.845)	(0.458)	
α_L	0.213***	-0.442***	0.426***	1.353***	0.887***	
	(0.361)	(1.158)	(0.275)	(0.196)	(0.274)	
β_L	2.724***	-1.731***	2.118***	2.716***	-0.596***	
	(1.887)	(1.582)	(2.216)	(1.247)	(0.528)	
AIC	-16.533	-1.960	-9.364	-3.578	-7.554	
6. TVP-SJC						
ω_U	-6.159***	-3.574***	1.385	-13.500	-18.447	
	(2.228)	(1.066)	(30.558)	(302.061)	(1128.418)	
α_U	15.987***	2.888***	-24.760	-0.015	-1.652	
	(6.640)	(6.010)	(188.986)	(1.006)	(470.200)	
β_U	1.096***	4.806***	8.511***	-0.059	-0.005	
	(1.526)	(2.856)	(2.725)	(2.313)	(1.723)	
ω_L	-3.937***	-15.293	-9.052***	-20.454***	-1.326***	
	(2.236)	(3.383)	(7.228)	(2.377)	(0.741)	
α_L	8.123***	-3.543	21.093***	-0.000	-3.359***	
	(7.671)	(16.172)	(21.569)	(1.000)	(2.942)	
β_L	1.691***	-0.008	3.768***	0.000	4.332***	
	(2.915)	(2.764)	(1.018)	(1.000)	(0.527)	
AIC	**-18.891**	-8.137	**-16.583**	-0.280	-6.339	
7. TVP-Student's-t						
Ψ_0	1.228***	0.218***	0.492***	0.353***	-0.036	
	(0.711)	(0.247)	(0.477)	(0.368)	(0.501)	
Ψ_1	0.571***	0.457***	1.307***	0.311***	0.808***	
	(0.315)	(0.395)	(0.514)	(0.404)	(0.715)	
Ψ_2	-2.265***	-0.091	-2.129***	-1.713***	-1.648***	
	(0.399)	(1.086)	(0.091)	(0.611)	(0.486)	
ν	5.000***	5.000***	5.000***	5.000***	3.138***	
	(2.371)	(1.867)	(1.952)	(1.701)	(1.605)	
AIC	-14.796	-1.710	-10.192	1.965	**-15.093**	

Notes: The table displays the fit of multiple copulas with time-varying parameters. In identifying the Copula the best fits the data, we employ the Akaike information criterion (AIC), "*, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Downside and upside VaR and CoVaR for returns on the US and Chinese stock sectors (Pre-COVID-19).

	Downside VaR	CoVaR	H_0 = CoVaR = VaR H_1 = CoVaR<VaR	Upside VaR	CoVaR	H_0 = CoVaR = VaR H_1 = CoVaR>VaR
Panel: A From the United States to China						
CSI 300 Index	-1.967	-1.156	0.000	1.935	5.357	0.954***
	(0.034)	(0.020)	[1.000]	(0.032)	(0.141)	[0.000]
Consumer Discretionary	-2.193	-2.819	0.425***	2.397	2.920	0.454***
	(0.038)	(0.071)	[1.000]	(0.038)	(0.051)	[0.000]
Consumer Staples	-2.371	-1.703	0.000	2.571	4.420	0.678***
	(0.028)	(0.029)	[1.000]	(0.038)	(0.140)	[0.000]
Energy	-1.664	-3.695	1.000***	1.433	2.300	0.879***
	(0.016)	(0.052)	[0.000]	(0.016)	(0.032)	[0.000]
Financials	-2.044	-1.704	0.000	2.006	4.639	0.914***
	(0.027)	(0.029)	[1.000]	(0.027)	(0.109)	[0.000]
Health Care	-2.414	-1.437	0.000	2.286	3.181	0.477***
	(0.034)	(0.026)	[1.000]	(0.031)	(0.120)	[0.000]
Industrials	-2.113	-1.232	0.000	1.940	4.092	0.724***
	(0.035)	(0.021)	[1.000]	(0.033)	(0.148)	[0.000]
Information Technology	-3.236	-2.746	0.000	3.356	8.054	1.000***
	(0.028)	(0.027)	[1.000]	(0.031)	(0.153)	[0.000]
Materials	-2.082	-3.718	0.810***	2.009	4.151	0.891***
	(0.035)	(0.064)	[0.000]	(0.033)	(0.102)	[0.000]
Telecommunication	-3.004	-6.054	0.885***	3.451	3.194	0.006
	(0.044)	(0.149)	[0.000]	(0.047)	(0.042)	[0.994]
Utilities	-1.597	-1.213	0.000	1.219	2.489	0.897***
	(0.012)	(0.009)	[1.000]	(0.010)	(0.067)	[0.000]
Panel: B From China to the United States						
S & P 500 Index	-1.385	-0.980	0.000	1.196	2.461	0.569***
	(0.053)	(0.038)	[1.000]	(0.043)	(0.094)	[0.000]
Consumer Discretionary	-1.783	-1.061	0.000	1.316	2.037	0.414***
	(0.053)	(0.032)	[1.000]	(0.112)	(0.253)	[0.000]
Consumer Staples	-1.313	-0.832	0.000	1.019	2.013	0.558***
	(0.029)	(0.018)	[1.000]	(0.032)	(0.083)	[0.000]
Energy	-2.533	-1.766	0.000	1.932	3.586	0.879***
	(0.038)	(0.027)	[1.000]	(0.031)	(0.055)	[0.000]
Financials	-1.657	-1.184	0.000	1.511	2.758	0.575***
	(0.056)	(0.040)	[1.000]	(0.050)	(0.094)	[0.000]
Health Care	-1.641	-0.957	0.000	1.331	1.880	0.414***
	(0.040)	(0.022)	[1.000]	(0.031)	(0.074)	[0.000]
Industrials	-1.820	-1.157	0.000	1.482	2.811	0.546***
	(0.051)	(0.030)	[1.000]	(0.044)	(0.089)	[0.000]
Information Technology	-2.024	-1.370	0.000	1.856	3.989	0.598***
	(0.071)	(0.049)	[1.000]	(0.065)	(0.149)	[0.000]
Materials	-1.802	-1.215	0.000	1.425	3.120	0.632***
	(0.042)	(0.026)	[1.000]	(0.045)	(0.103)	[0.000]
Telecommunication	-1.764	-1.120	0.000	1.518	2.168	0.351***
	(0.047)	(0.031)	[1.000]	(0.046)	(0.064)	[0.000]
Utilities	-1.426	-1.044	0.000	1.284	2.303	0.724***
	(0.023)	(0.018)	[1.000]	(0.020)	(0.062)	[0.000]

Notes: The table shows the magnitude of the spillovers. The values in brackets are standard errors. Values in [] are the p-values of the Kolmogorov-Smirnov (K-S) test.

Table 7
Downside and upside VaR and CoVaR for returns on the US and Chinese stock sectors (During COVID-19).

	Downside VaR	CoVaR	$H_0 = CoVaR = VaR$ $H_1 = CoVaR<VaR$	Upside VaR	CoVaR	$H_0 = CoVaR = VaR$ $H_1 = CoVaR>VaR$
Panel: A From the United States to China						
CSI 300 Index	-2.088	-1.204	0.000	2.051	2.773	0.462***
	(0.061)	(0.035)	[1.000]	(0.058)	(0.095)	[0.000]
Consumer Discretionary	-2.413	-2.210	0.008	2.619	6.974	0.639***
	(0.074)	(0.073)	[0.991]	(0.075)	(0.354)	[0.000]
Consumer Staples	-2.509	-1.785	0.000	2.708	8.066	0.950***
	(0.049)	(0.036)	[1.000]	(0.065)	(0.235)	[0.000]
Energy	-1.972	-3.806	0.933***	1.730	3.531	0.941***
	(0.031)	(0.083)	[0.000]	(0.029)	(0.087)	[0.000]
Financials	-2.195	-2.384	0.336***	2.158	9.205	1.000***
	(0.046)	(0.046)	[0.000]	(0.046)	(0.218)	[0.000]
Health Care	-3.187	-1.901	0.000	2.572	4.988	0.361***
	(0.0257)	(0.0156)	[1.000]	(0.209)	(0.372)	[0.000]
Industrials	-2.155	-1.294	0.000	1.980	7.194	1.000***
	(0.057)	(0.034)	[1.000]	(0.054)	(0.199)	[0.000]
Information Technology	-3.364	-2.532	0.000	3.464	8.476	0.916***
	(0.049)	(0.061)	[1.000]	(0.056)	(0.294)	[0.000]
Materials	-2.417	-3.282	0.353***	2.326	5.356	0.815***
	(0.067)	(0.163)	[0.000]	(0.064)	(0.126)	[0.000]
Telecommunication	-3.429	-4.104	0.277***	3.901	4.750	0.193
	(0.090)	(0.129)	[0.000]	(0.095)	(0.224)	[0.010]
Utilities	-1.644	-1.582	0.118	1.259	2.679	0.857***
	(0.020)	(0.037)	[0.182]	(0.017)	(0.094)	[0.000]
Panel: B From China to the United States						
S & P 500 Index	-3.504	-2.436	0.000	2.906	4.217	0.202***
	(0.344)	(0.241)	[1.000]	(0.279)	(0.418)	[0.007]
Consumer Discretionary	-3.475	-2.001	0.000	2.580	7.948	0.513***
	(0.305)	(0.176)	[1.000]	(0.232)	(0.788)	[0.000]
Consumer Staples	-3.130	-2.104	0.000	2.695	6.723	0.824***
	(0.308)	(0.205)	[1.000]	(0.278)	(0.235)	[0.000]
Energy	-5.840	-3.992	0.000	4.841	10.371	0.403***
	(0.443)	(0.301)	[1.000]	(0.383)	(0.755)	[0.000]
Financials	-4.514	-3.298	0.000	4.024	9.715	0.462***
	(0.396)	(0.290)	[1.000]	(0.351)	(0.850)	[0.000]
Health Care	-3.504	-2.188	0.000	2.906	5.369	0.345***
	(0.344)	(0.216)	[1.000]	(0.279)	(0.502)	[0.000]
Industrials	-4.293	-2.824	0.000	3.588	10.441	0.504***
	(0.378)	(0.248)	[1.000]	(0.322)	(0.882)	[0.000]
Information Technology	-4.003	-2.695	0.000	3.507	8.283	0.387***
	(0.359)	(0.249)	[1.000]	(0.315)	(0.859)	[0.000]
Materials	-3.749	-2.399	0.000	3.485	7.477	0.471***
	(0.287)	(0.182)	[1.000]	(0.298)	(0.568)	[0.000]
Telecommunication	-3.075	-1.883	0.000	2.603	5.075	0.370***
	(0.244)	(0.150)	[1.000]	(0.213)	(0.467)	[0.000]
Utilities	-3.672	-3.419	0.017	3.226	6.791	0.378***
	(0.326)	(0.329)	[0.966]	(0.282)	(0.689)	[0.000]

Notes: The table shows the magnitude of the spillovers. The values in brackets are standard errors. Values in [] are the p-values of the Kolmogorov-Smirnov (K-S) test.

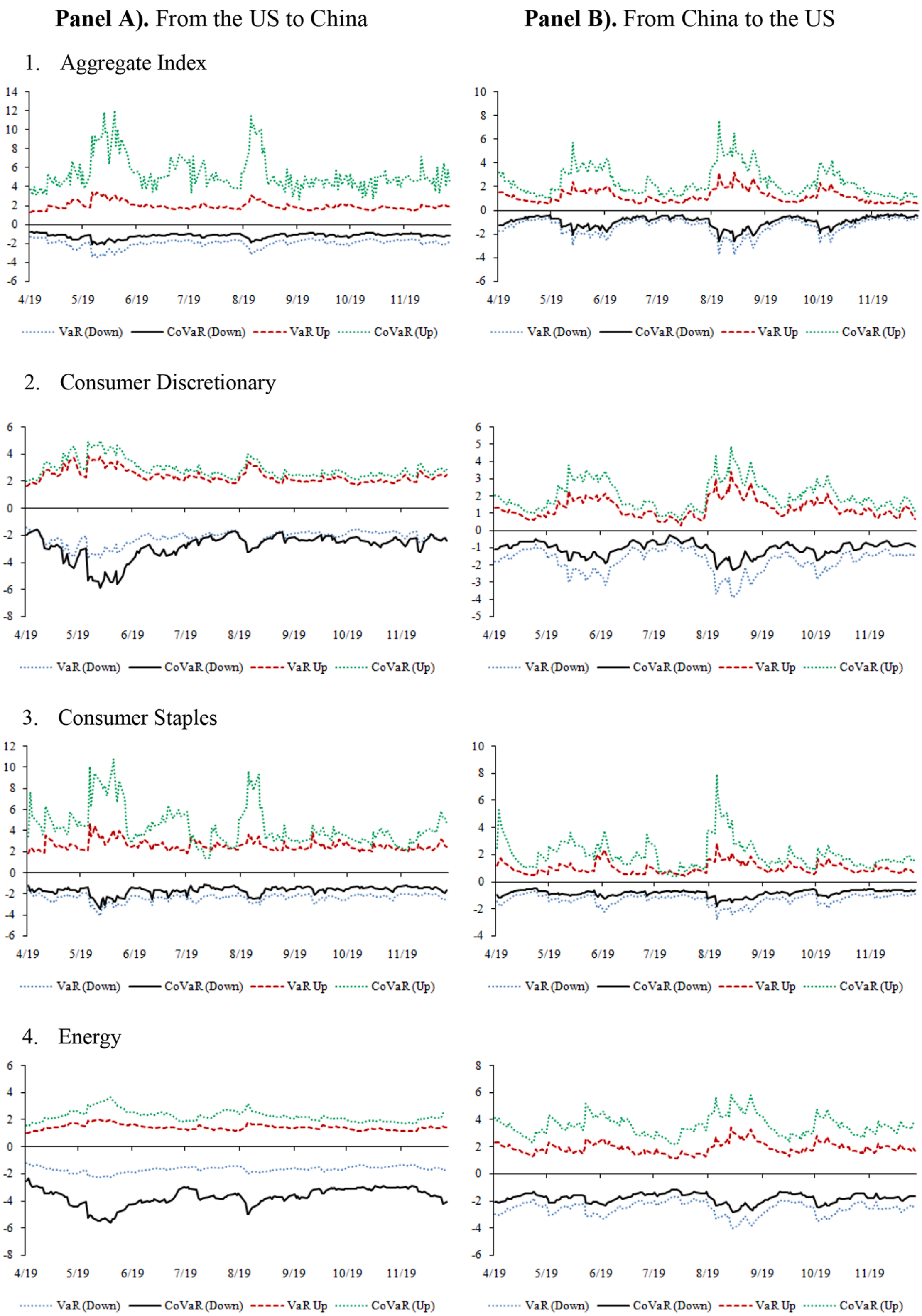
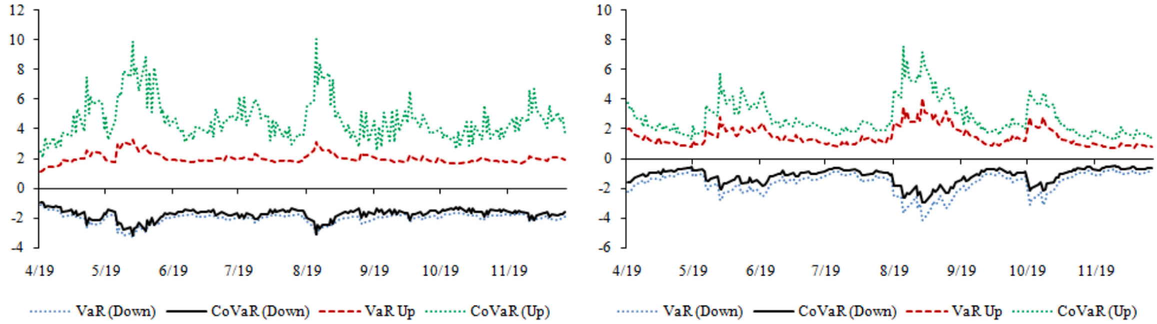
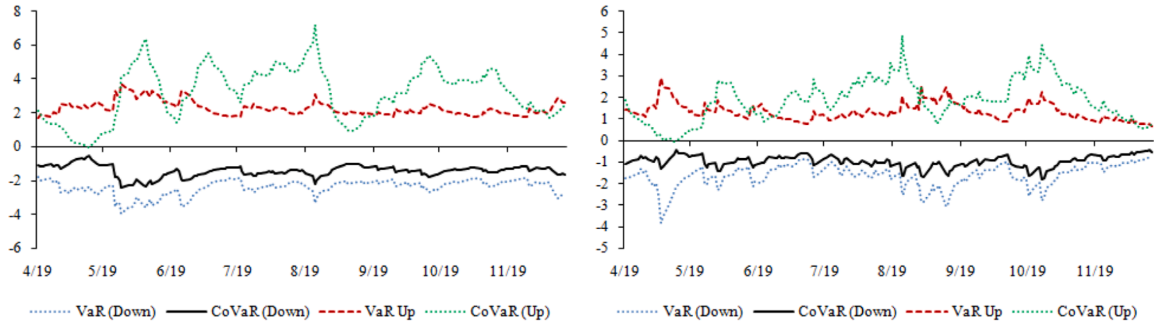


Fig. 1. Risk spillover between US and Chinese stock sector pairs (Pre-COVID-19 pandemic).

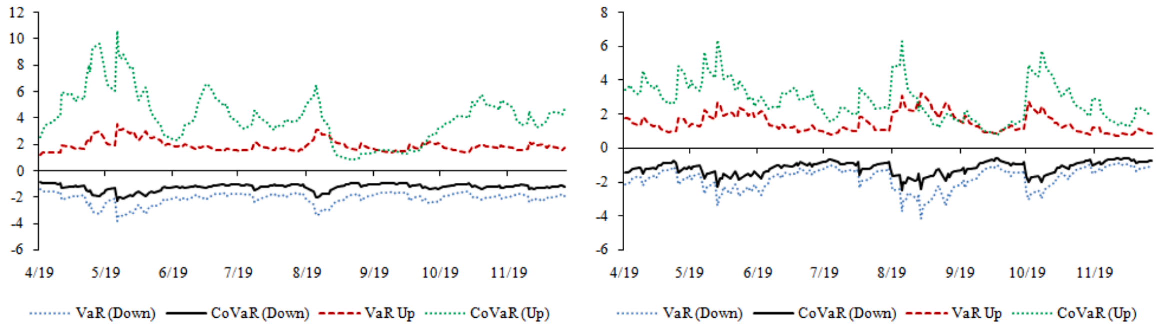
5. Financials



6. Health Care



7. Industrials



8. Information Technology

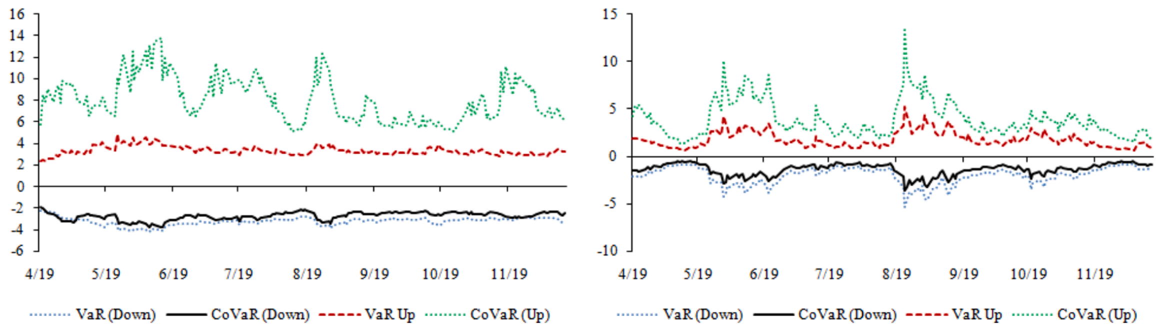


Fig. 1. (*continued*).

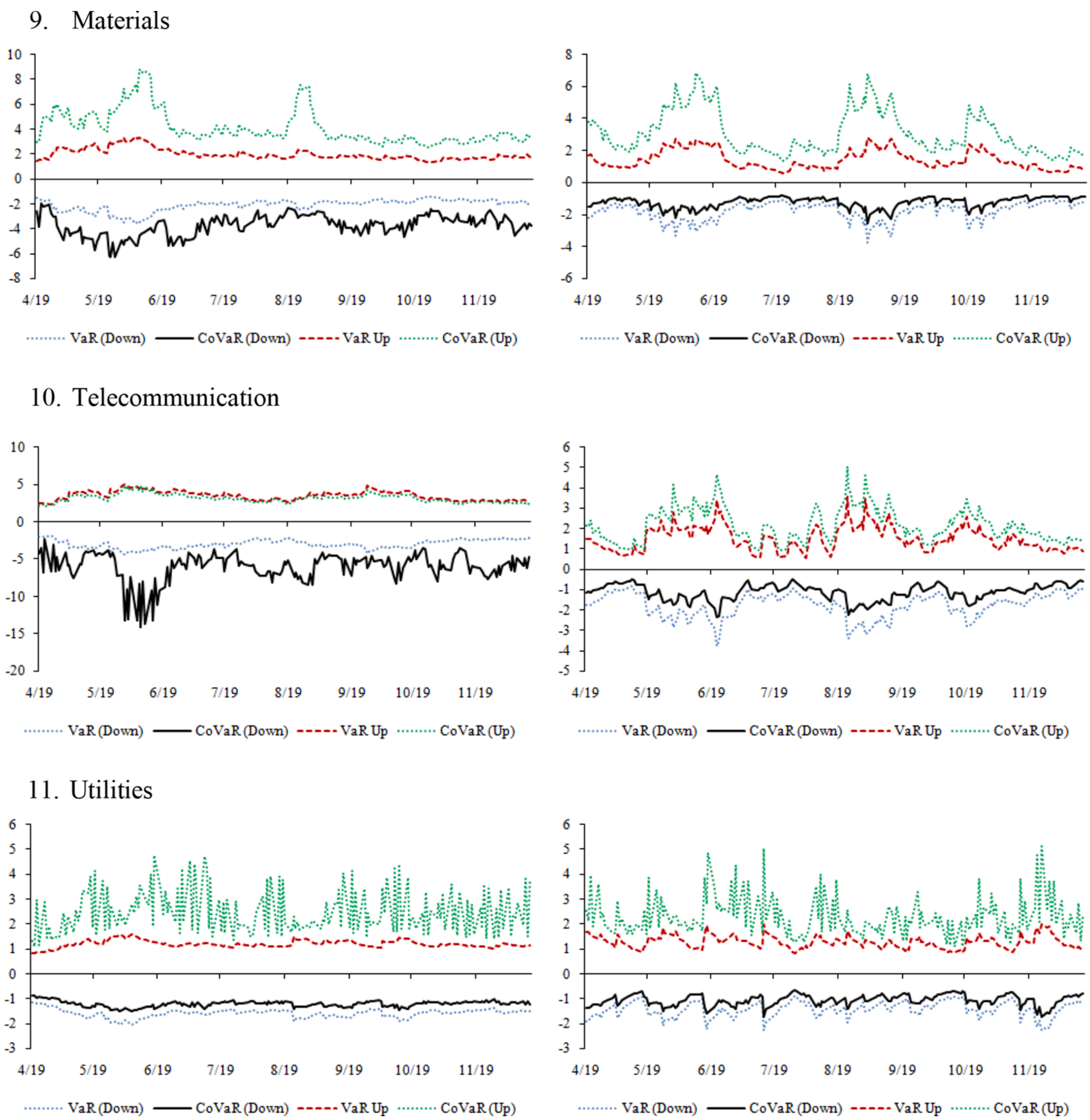


Fig. 1. (*continued*).

between downside/upside VaRs and CoVaRs for almost all cases, confirming the presence of significant spillover effects.

4. Conclusion

This paper examines the impacts of COVID-19 outbreak on the dependence structure and risk spillovers among aggregate and ten stock sectors in the US and China. We apply the copula functions and both VaR and CoVaR to achieve our objectives.

The results show zero tail dependence for Financials, Health Care, and Industrials sectors during the pre-COVID-19 pandemic. For the aggregate index and Consumer Staples, we find symmetric upper and lower tail dependence. In contrast, Telecommunication and Consumer Discretionary (Utilities) sectors exhibit lower tail dependence (independence) and upper tail independence (dependence). The Energy, Information Technology, and Materials sectors reveal asymmetric tail dependence. More importantly, we find strong evidence of asymmetric tail dependence during the COVID-19 period. This result indicates that the global health crisis affects the dependence structure between the US and China sectors. Finally, we report evidence of bidirectional risk spillovers from the US to China and vice versa. The magnitude of spillovers is higher from the US to China during pre-COVID-19 and from China to the US during the COVID-19 pandemic. The risk spillovers reaches its maximum level from March 2020 to April 2020. These findings assist investors in their decision-making process and policy makers in stabilizing the spillovers among sectors in the climate of the human health crisis.

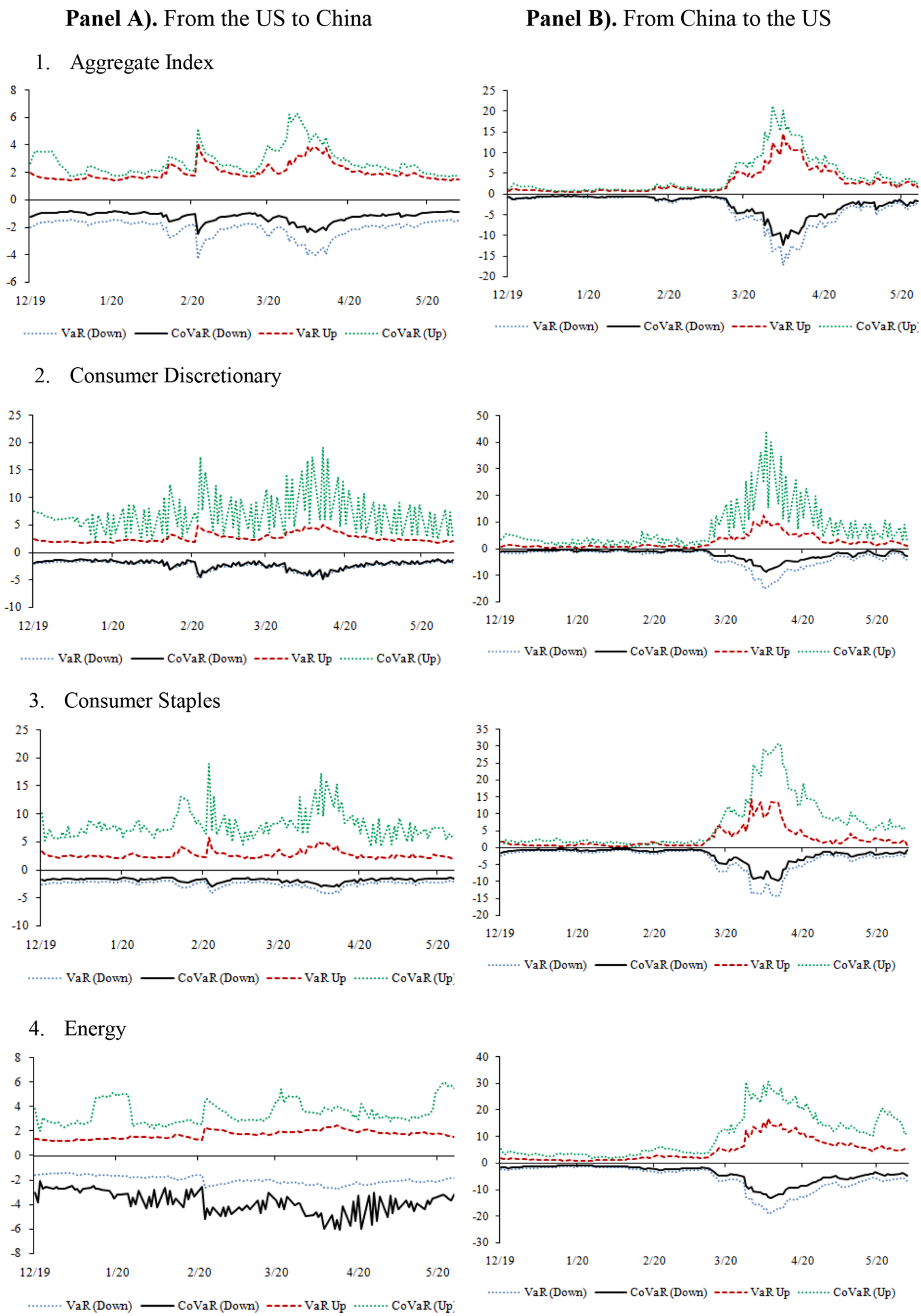
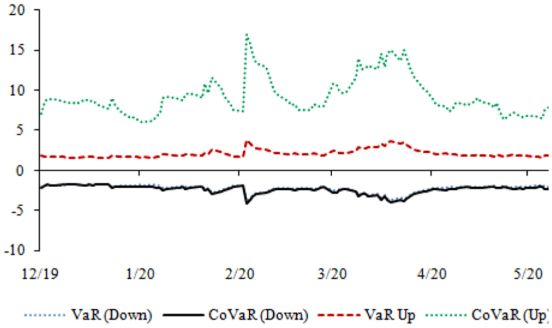
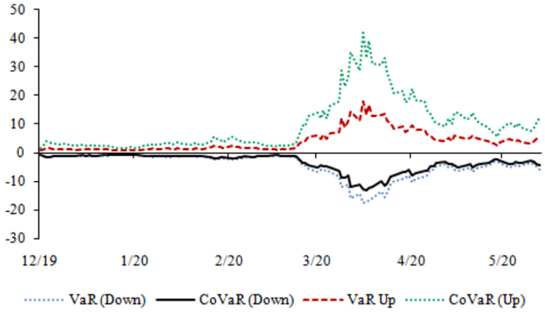


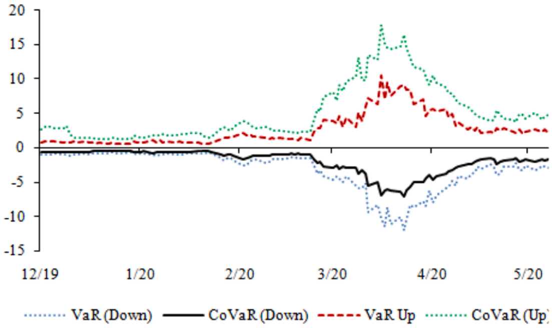
Fig. 2. Risk spillover between United States and Chinese stock sector pairs (During COVID-19 pandemic).

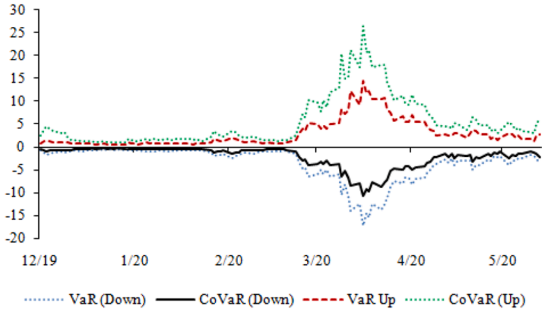
5. Financials



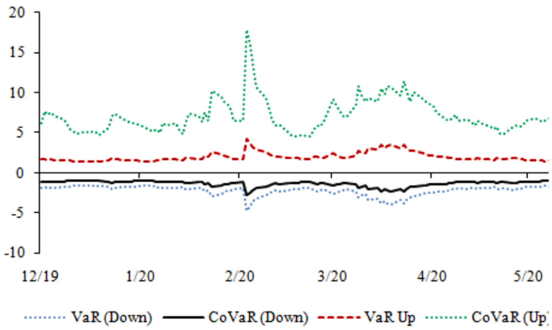


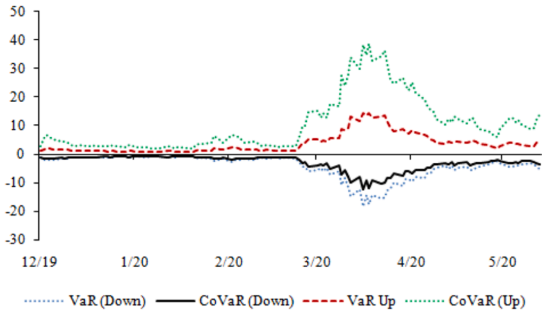
6. Health Care



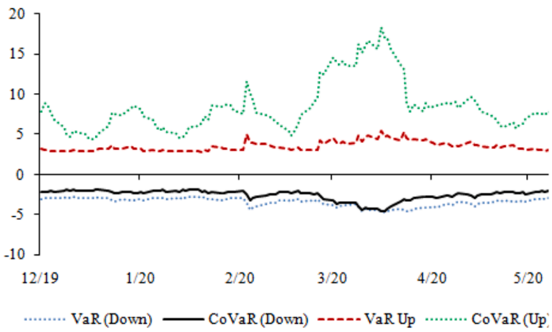


7. Industrials





8. Information Technology



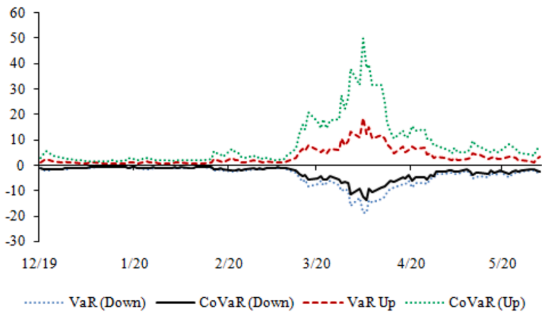
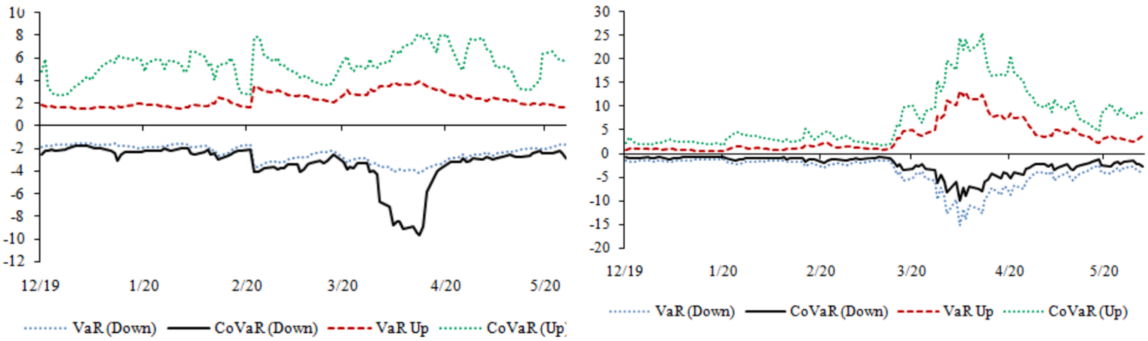
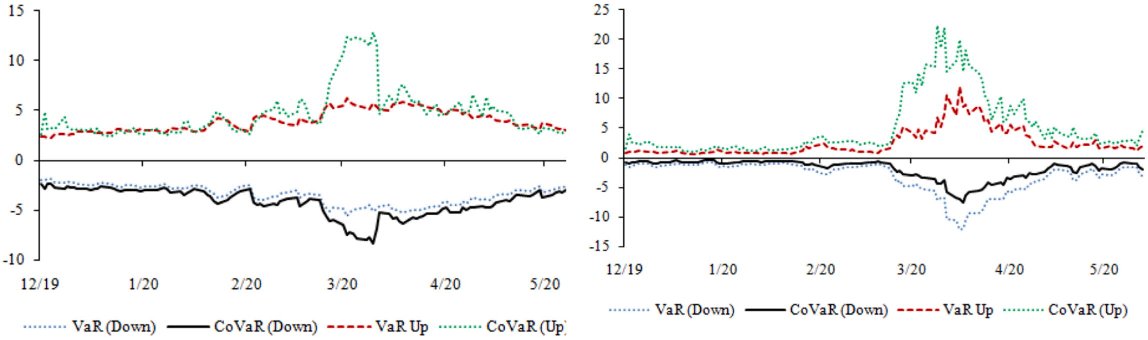


Fig. 2. (*continued*).

9. Materials



10. Telecommunication



11. Utilities

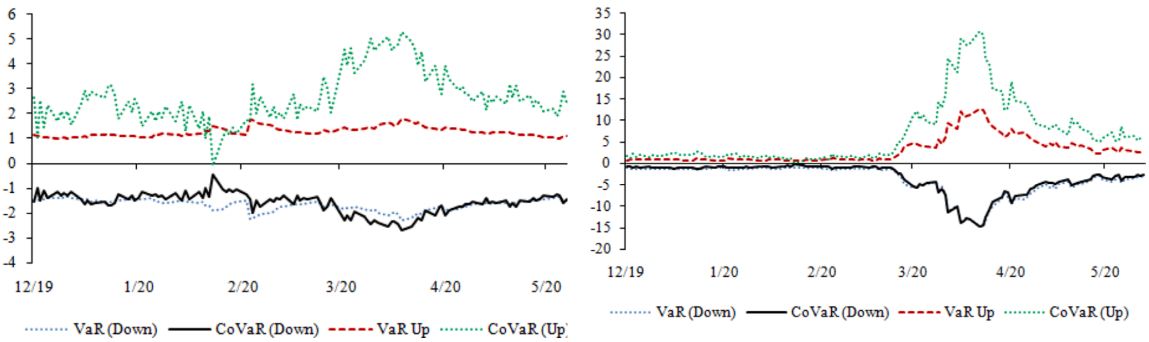


Fig. 2. (*continued*).

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